A graph data model facilitates analysis of collaboration in an emergency department

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Aims

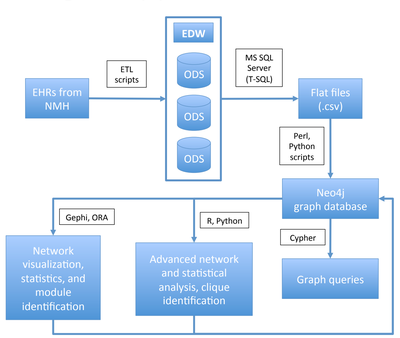
- To create a high-throughput analysis framework for emergency department encounter workflow based on a graph data model
- To use this model to facilitate quantification and measurement of provider collaboration

Introduction

- Healthcare is a complex system of interactions between patients and providers on many levels.
- During an encounter, a variety of personnel perform a different but overlapping set of activities in a cooperative effort to facilitate patient care.
- Recently, graph databases have been used to explore and gain knowledge from complex data sets in many industries.
- The inherent connectivity of the graph data model makes it ideal for exploring collaborative relationships between providers.

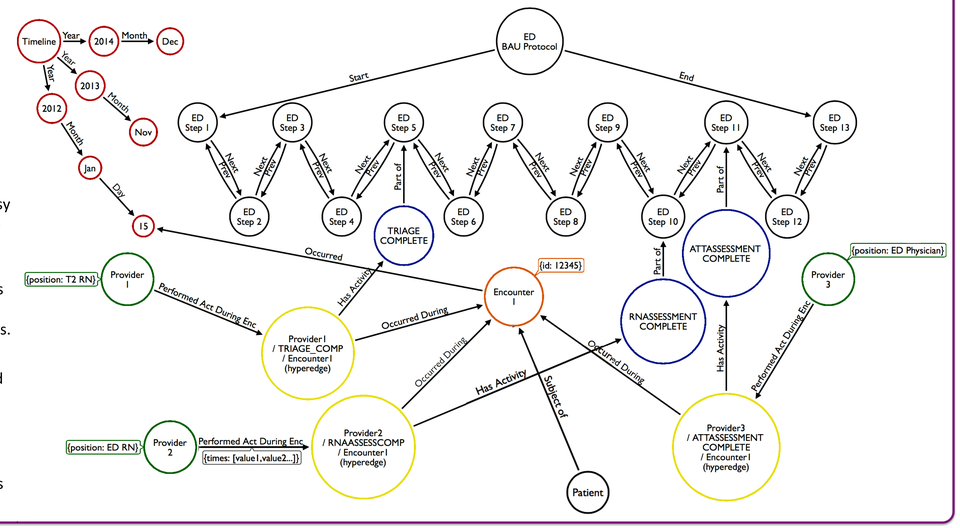
Methods

- We identified workflow in the ED and translated this to a labeled property graph model.
- From Northwestern Medicine's Enterprise Data Warehouse (NM EDW) we extracted 259,289 ED encounters from 2012 - 2014 involving 155,976 patients and approximately 11,676 providers performing 75,220,941 activities.
- Our data management pipeline is shown below.



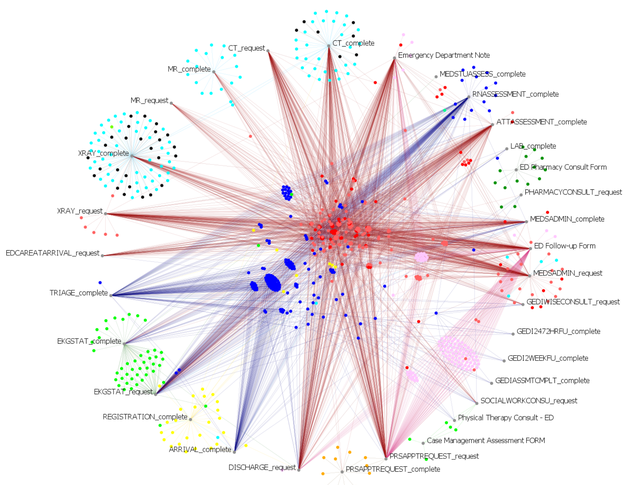
Labeled Property Graph Model

- **Right:** An example of our graph data model showing the activities of three providers during one encounter. Nodes are colored by label: **ED workflow, encounter, hyperedge, provider, time, and activity**.
- **Advantages of graph databases:**
  - Inherent connectivity of all data yields faster query times and avoids the "join problem".
  - Lack of a predefined schema allows for easy updating and modification of the model; no table alterations required.
  - In the labeled property graph model both nodes and relationships can have properties (key-value pairs); this creates a rich data representation and facilitates ad hoc queries.
- **Hyperedges:**
  - Identify specific instances of an activity and allow relationships between $n > 2$ entities (i.e., Provider P performed Activity A during encounter E).
  - Add flexibility by allowing data subsetting, e.g., an analysis of all providers and activities associated with specific workflow steps.

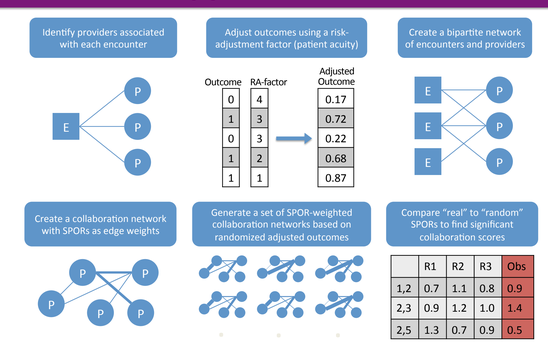


Provider-Activity Network

- **Below:** Activities in the ED workflow (**grey nodes**, clockwise from the bottom left in order of occurrence) and a subset of the providers who performed them. Providers are colored by position type: **Physician, Res/Fellow, Med Student, Nurse, ED assistant, Pharmacy, RAD, ED registration, Physician Referral Services (PRS), Reg/Sched SU**.
- The number of activities performed varies widely across provider types, with nurses, physicians, and res/fellows carrying out the largest number of activity types.
- Some provider types (e.g., **Nurse**) are divided into communities based on similar subsets of activities performed by individuals.



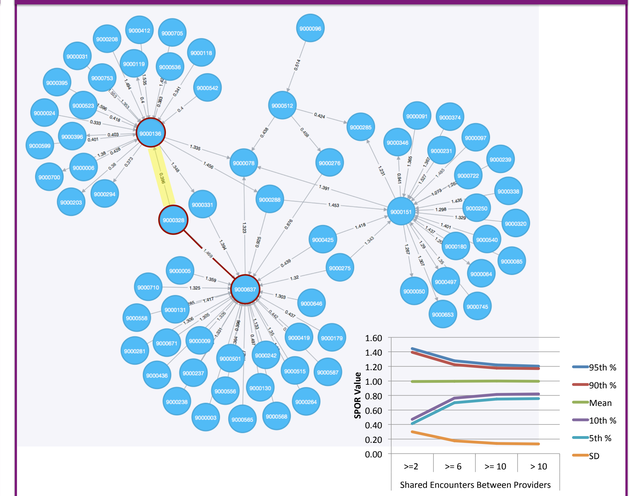
Applications[1,2]



	R1	R2	R3	Obs
1,2	0.7	1.1	0.8	0.9
2,3	0.9	1.2	1.0	1.4
2,5	1.3	0.7	0.9	0.5

- Extending our previous work[4], we developed a novel parameter, the ***Shared Positive Outcome Ratio*** **(SPOR)**, an objective composite measure that quantifies the concentration of positive outcomes between two providers over a set of shared patient encounters.[1]
- Taking a subset of the ED data, we constructed a bipartite network of 2,750 providers and 6,823 encounters using patient acuity as a risk adjustment factor (RA-factor) and likelihood to recommend (LTR) as an outcome.
- From this we created a network model to assess pairwise collaboration between healthcare providers who shared > 5 patients (580 providers, 5,642 collaborations).
- We identified collaborations at the high (top 5%) and low (bottom 5%) SPOR extremes (higher or lower than expected patient satisfaction rates, respectively).
- We found 29 providers with > 5% of their collaborations in the high-scoring group (38 in low-scoring group). Fifteen providers belonged to both groups.
- Providers in the high-scoring group had both a higher average number of associated encounters (255 vs. 220) and a higher percentage of total encounters with positive outcomes (61% vs. 57%) than those in the low-scoring group.

Results



- In terms of patient satisfaction, collaborative relationships between pairs of providers are not equal.
- Individual providers are often involved in both high- and low-scoring relationships.
- An increase in the number of shared encounters between a pair of providers may improve collaboration in some cases.

Related Research / Future Directions

- To continue to apply our collaboration evaluation method to new clinical domains, most recently cardiology [2]
- Using our graph model and database to facilitate improved FMEA practices [3]
- Extending the SPOR metric to teams of ≥ 3 providers
- Our graph model could be expanded to include auxiliary health information such as genomic and proteomic data, regulatory pathways, and precision medicine information for more in-depth analyses.

References

1. Carson, Gravenor, Scholtens, Frailey, Shier Kricke, and Soulakis. **An outcome-weighted network model for quantifying and measuring collaboration.** *In preparation.*
2. Carson, Scholtens, Frailey, Shier Kricke, Benacka, Ahmad, Mutharasan, Kansal, Anderson, Yancy, and Soulakis. **Quantifying Teamwork at Hospital Discharge for Readmissions Reduction: A Network Analytics Approach.** Quality of Care and Outcomes Research (QCOR) Conference, Feb. 28 – March 1, 2016, Phoenix, AZ. *Submitted.*
3. Kricke, Carson, Lee, Benacka, and Soulakis. **Leveraging Electronic Health Record Documentation for Failure Mode and Effects Analysis Team Identification on an Inpatient Cardiology Unit**. *In preparation.*
4. Soulakis, Carson, Lee, Schneider, Skeehan, and Scholtens. **Visualization of multidisciplinary, collaborative care for hospitalized heart failure patients**. *J Am Med Inform Assoc*, Special Issue on Visual Analytics in Healthcare. 2015 Feb 20.

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